# Despeckling of Ultrasound Imaging Using Median Regularized Coupled PDE

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***Abstract* - This paper presents an approach for reducing speckle in ultrasound images using Coupled Partial Differential Equation (CPDE) which has been obtained by uniting second-order and the fourth-order partial differential equations. Using PDE to reduce the speckle is the noise-smoothing methods which is getting attention widely, because PDE can keep the edge well when it reduces the noise. We also introduced a median regulator to guide energy source to boost the features in the image and regularize the diffusion. The proposed method is tested in both simulated and real medical ultrasound images. The proposed method is compared with SRAD, Perona Malik diffusion and Non linear coherent diffusion methods, our method gives better result in terms of CNR, SSIM and FOM.**

***Index Terms* – Ultrasound, Speckle, PDE, median filter,**

## I. INTRODUCTION

ULTRASOUND speckle is the result of the diffuse scattering, which occurs when an ultrasound pulse randomly interferes with the small particles or objects on a scale comparable to the sound wavelength. Speckle is an inherent property of an ultrasound image, and is modeled as spatial correlated multiplicative noise. In most cases, it is considered a contaminating factor that severely degrades image quality. To improve clinical diagnosis, speckle reduction is generally used for two applications: visualization enhancement and auto-segmentation improvement. Most speckle filters are developed for enhancing visualization of speckle images [1]–[3] including temporal averaging, median filtering, adaptive speckle reduction (ASR) and wavelet based methods [4]-[5], frequency compounding methods [6]-[7].

However, above methods could not succeed to balance between speckle suppression and feature preservation due to the complexity of speckle statistics. The comparative analysis [8] and review methods [9] also says that a technique that relies on a more accurate model for removing speckle noise while preserving image feature well would be rather valuable for practical use improve image simplification, which is in turn very beneficial in automated object detection

## II. BACKGROUND OF PDE

The use of partial differential equations (PDE) in image processing has grown significantly over the past years. Its basic idea is to deform an image, a curve or a surface in a partial differential equation framework, and to approach the expected result as a solution to this equation.

P. Perona and J. Malik put forward an anisotropic diffusion (AD) equation to smooth a noisy image:

$$\frac{\partial u(x,y,t)}{\partial t} = div\,(g|\nabla u(x,y,t)|)\nabla u(x,y,t) \qquad (1)$$

where $\partial u$(x,y,t) :Ω,X→(0,+∞)→$R$ is a scale image, g(|∇u|) is a decreasing function of the gradient. Their work made an important influence on this field.

2D SRAD takes the format of the PDE of conventional anisotropic diffusion. Given an intensity image $I_0$(x, y) having none zero-valued intensities over the image domain U, the continuous form of SRAD is expressed as follows [10]

$$\begin{cases} \dfrac{\partial I(x,y,t)}{\partial t} = div[c(x,y,:t)\nabla I(x,y,t)] \\ I(x,y:0) = I_0(x,y), (\partial I(x,y;t)/\partial\Omega = 0 \end{cases} \qquad (2)$$

where ∂Ω denotes the border of Ω, $n^{\rightarrow}$ is the outer normal to the ∂Ω, c(x) is the diffusion coefficient, and q is the ICOV.

Both P-M diffusion and SRAD introduce blocky effects in image. So Yu-Li and M.Kaveh [11] proposed a fourth-order partial differential equation. This equation can reduce the noise, at the same time it can keep the image edge better. The PDE is:

$$\frac{\partial I}{\partial t} = -\nabla^2[g(|\nabla^2 I|)\nabla^2 I] = -\nabla[g(\Delta I)] \qquad (3)$$

Where $g(x) = \dfrac{1}{[1+(s/k)^2]}$ , k is constant.

The advantage of using fourth-order PDE in denoising image is it removes the blocky effects that made by second-order nonlinearity diffusion equation.

## III. PROPOSED METHOD

The coupled PDE based on second-order and fourth-order PDE is :

$$\frac{\partial I}{\partial t} = -\nabla[g_1(\Delta I)\nabla I + a.g_2(\Delta I)\Delta\nabla I] \qquad (4)$$




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Where ‘a’ is the coupled coefficient and the functions $g_1$, $g_2$ are plus and non-increasing function

The median filter is a well-known “edge preserving” nonlinear filter. It removes the extreme data while producing a smoothed output. We propose to use a median regulator in coupled PDE, which combines both medina filtering and strength of unity of second order and fourth order Partial Differential equation.

The proposed technique is defined by the following relations:

$$\frac{\partial I(x,y,t)}{\partial t} = -\nabla[g_1(\Delta I)\nabla I + a.g_2(\Delta I)\Delta\nabla I] + \alpha f$$
$$I(x,y,t)_{t=0} = I$$
$$\partial_n I = 0, f = median(I). \quad (5)$$

Speckle noise is signal-dependent noise. Typically, the bright regions have stronger noise than the dark regions. The source term *f* provides a boosting force to guide (or normalize) the diffusion evolution and also accelerate the convergence rate compared to natural diffusion. α is control coefficient whose value lies between 0 and 1

The function $g_1$, $g_2$ are defined as

$$g_1(x) = \exp(-[x/k_1]^2),$$
$$g_2(x) = \frac{1}{(1+(x/k_2)^2)}. \quad (6)$$

Where $k_1$, $k_2$ are constants. The coupled PDE removes the noise and keeps the edges, regulator act as an accelerating force to produce an image with less noise and enhanced structure

## IV. IMPLEMENTATION AND RESULT

The proposed method is tested on a simulated fetus image using Field-II ultrasound simulation software and a real ultrasound liver image.

Throughout this paper, we take multiplicative noise as the model for speckle. The degraded intensity for each pixel will be

$$I_{i,j} = f_{i,j} u_{i,j} \quad (7)$$

Where $f_{i,j}$ is the intensity at pixel ( $i, j$ )in the original image, $u_{i,j}$ the multiplicative noise, and $I_{i,j}$ is the intensity at pixel ( $i, j$ ) in the observed image

The structure similarity (SSIM), Contrast to noise ratio (CNR), Pratt’s Figure of Merit (FOM) are calculated to compare the performance of proposed method with SRAD, Perona Malik diffusion and Non linear coherent diffusion methods.

The structure similarity (SSIM) [12] was used to evaluate the overall processing quality

$$SSIM = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \quad (8)$$

Where $\mu_i$ and $\sigma_i$ are the mean and standard deviation of intensities of pixels in a local window, and is the constant to avoid instability. All involved parameters were set as suggested in [13]. The value of SSIM varies between 0 and1, with unity for ideal processing quality, i.e., when the filtered image is equal to the reference image.

The contrast-to-noise-ratio (CNR) or lesion signal-to-noise ratio [13], [14], was computed by

$$CNR = \frac{|\mu_1 - \mu_2|}{\sqrt{\sigma_1^2 + \sigma_2^2}} \quad (9)$$

Where $\mu_1$ and $\sigma_1^2$ are the mean and variance of intensities of pixels in a region of interest (ROI), and $\mu_2$ and $\sigma_2^2$ are the mean and variance of intensities of pixels in a background region that has the same size as the ROI to be compared with.

Edge preservation or edge enhancement can be quantitatively evaluated by Pratt’s figure of merit (FOM).

$$FOM = \frac{1}{\max\{\hat{N}, N_{ideal}\}} \sum_{i=1}^{\hat{N}} \frac{1}{1 + d_i^2 \lambda} \quad (10)$$

Where $\hat{N}, N_{ideal}$ are the numbers of detected and ideal edge pixels, respectively. *di* is the Euclidean distance between the *i*th detected edge pixel and the nearest ideal edge pixel. *Λ* is a constant typically set to 1/9. The dynamic range of FOM is between [0, 1]. Higher value indicates better edge matching between processed image and the ideal image.

In the implementation of median regularized coupled PDE method the following values are selected for the parameters: $k_1$=0.03, $k_2$=0.04 and α=1.The mask size of 3X3 is chosen to calculate median regulator.

The result of proposed method, NCD, SRAD and Perona Malik diffusion on Field II ultrasound simulation software generated fetus image are shown in fig. 1. The same methods are tested on and real ultrasound liver images and the results are shown in fig.2.Comparision of performance measure are shown in Table.1.Image profile along 154th row of various filtered images are shown in the fig.3

## V. DISCUSSION AND CONCLUSION

The result processed by the new method is much sharper in terms of edge preservation and smoother in terms of speckle noise reduction than the other three filtered results. The execution time is also much shorter than the other methods. For quantitative quality evaluation, we provide three metrics SSIM, CNR and FOM. Table.1. shows the evaluation results for the processed image.




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The FOM value indicates that the new method is better than other methods in terms of edge preserving ability. CNR and SSIM values indicate that the new method gives a better processing result in terms of structure preservation and contrast enhancement.

In order to keep the image feature better we adopted coupled PDE by uniting second order and fourth order PDE, Further more we added a median regulator to accelerate the convergence rate. The proposed Median regularized coupled PDE provides improved result over other methods in terms many parameters. Therefore it has a wide applicability in practice.

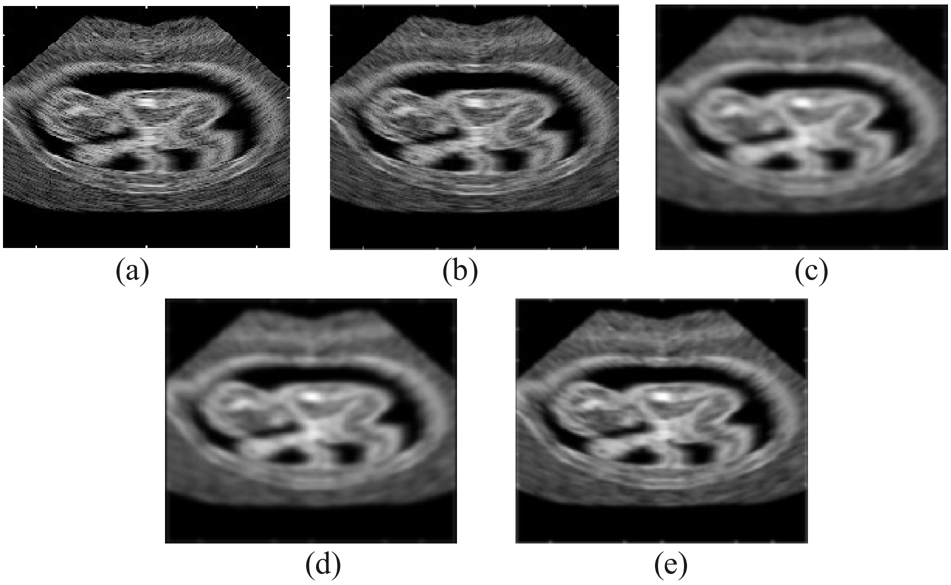


Fig.1 Result on simulated image (a) Original Noisy Image , Image filtered by (b) Perona Malik Diffusion (c) Non Linear Coherent Diffusion (NCD) (d) SRAD (e) Medial Regularized Coupled PDE

Table 1 Comparison of Performance Measure

| | NOISY IMAGE | Perona Malik | NCD | SRAD | Proposed |
|---|---|---|---|---|---|
| **CNR** | 0.52±0.07 | 0.88±0.47 | 1.52±0.007 | 1.77±0.37 | **2.56±0.46** |
| **SSIM** | 0.4322±0.0028 | 0.7279±0.0031 | 0.7422±0.0035 | 0.7531±0.0039 | **0.8122±0.0038** |
| **FOM** | - | 0.6543 | 0.5873 | 0.6546 | **0.9067** |

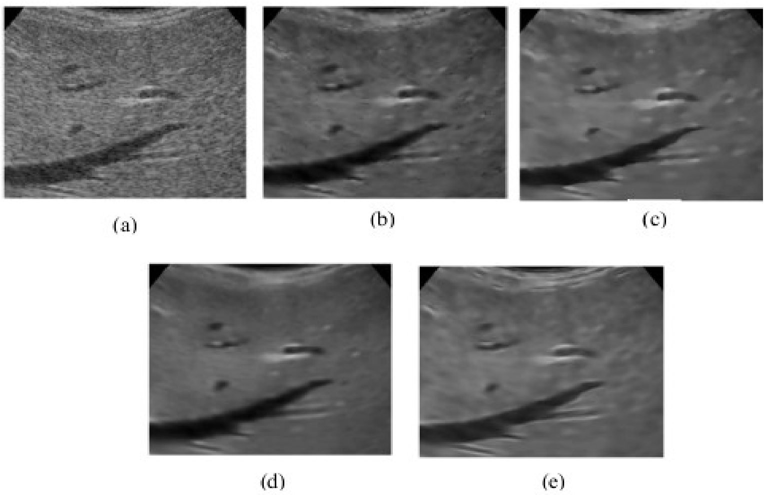


Fig.2. Result on real ultrasound image (a) Original Noisy Image , Image filtered by (b) Perona Malik Diffusion (c) Non Linear Coherent Diffusion (NCD) (d) SRAD (e) Medial Regularized Coupled PDE




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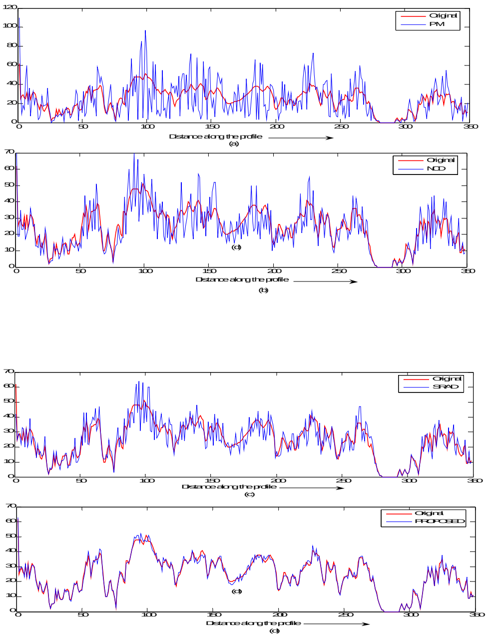

Fig.3 Profile of the filtered image along 154th row (a) Perona Malik Diffusion (b) Non Linear Coherent Diffusion (NCD) (c) SRAD (d) Proposed Medial Regularized Coupled PDE

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